Application of the Fuzzy Clustering Technique for Processing and Analysis of Medical Images

Alexander Stepanenko[1][0000-0002-3668-5828], Andrii Oliinyk[2][0000-0002-6740-6078], Ievgen Fedorchenko[3][0000-0003-1605-8066]

Department of Software Tools, National University "Zaporizhzhia Polytechnic", 64 Zhukovskoho str., Zaporizhzhia, Ukraine, 69063
[1]alex@zntu.edu.ua,[2]olejnikaa@gmail.com,
[3]evg.fedorchenko@gmail.com

Abstract. The problem of improving the efficiency of medical diagnostics is continuously present in the medical practice. The feasibility of using the mathematical tools for fuzzy logic as applied to the tasks of medical radiological images analysis is under investigation. The paper considers a new approach to the application of the fuzzy clustering technique for analysis and processing of medical images having various structures. The results of practical application of the new approach with the use of real medical images are shown.

Keywords: medical images, image recognition, segmentation, noise, fuzzy clustering, MCCPAO

1 Introduction

The ultrasonic imagining is one of the main and common methods of medical diagnostics [1], which places greater focus on the enhancement of sensitivity and reliability of the procedure for visualization of ultrasonic pulse-echo image. The paper [2] considers the opportunities for the enhancement of sensitivity of detection of the boundaries of low-contrast structures and neutralization of the impact of multiple reflection of ultrasonic pulses hindering the visual analysis of pulse-echo images. However, from the point of view of determination of homogeneity, roughness and regularity, the procedure for segmentation of the ultrasonic images is of the greatest interest. The issues of segmentation of different types of images fall within the domain of computer vision [3], but the presence of modulation speckle noises is the distinctive feature of ultrasound diagnostics. Therefore, the application of any method for segmentation of ultrasonic images should take into account the presence of this factor and come with the use of modulation noise filtering procedure.

Another distinctive feature of ultrasound diagnostics is the fact that the boundaries of the anatomical regions are "blurred" on the ultrasonic images, since the acoustical impedances of adjacent biological structures may be close or continuous variable. This fact necessitates the application of the fuzzy clustering techniques. The fuzzy clustering introduces the notion of fuzzy clusters and the function of membership of the objects thereto, which varies in the interval [0,1] and allows to estimate the degree of membership of the objects to the different classes. The fuzzy clustering is based on the FCM (Fuzzy C-Means) technique, which has many modifications [4]. The FCM technique is based on the use of ideas and mathematical tools for fuzzy logic, and it is widely used as applied to the tasks of medical radiological imaging analysis [5]. However, the information capabilities of the method as applied to the analysis of ultrasonic images have not been previously investigated.

2 Analysis of published data and problem definition

Recently, one of the urgent directions of the development of computer technology in medicine is the processing of digital images: improving image quality, restoring damaged images, recognizing individual elements. Ultrasonic (ultrasound) technique is the most common and allows you to diagnose a large number of dangerous conditions of human health.

To date, many leading research centers and laboratories have developed many image processing algorithms, including medical ones. When processing and analyzing images, the following main stages are distinguished: filtering, pre-processing, segmentation, recognition and diagnostics. The effectiveness of the subsequent stages of image processing directly depends on the results of filtering and pre-processing.

In [2], a clustering algorithm for medical images was proposed — a clustering algorithm using the dendrogram method. The proposed clustering method is based on the statistical pattern recognition method - the dendrogram method. This method consists in the fact that successively a pair of the closest points in the space of images is replaced by one point (center of gravity). The procedure is repeated as many times as needed until several points remain — the centers of the clusters. The dendrogram is a specialized type of diagram. Objects on the dendrogram are arranged in hierarchical levels to emphasize their mutual affinity. However, since this method was not previously used for clustering images, the authors made its substantial modification to solve the problem of distinguishing various image objects. To analyze the effectiveness of the developed algorithm, the authors of the article compare the proposed algorithm with the most common algorithm - the k-means clustering algorithm, which is used in most modern systems for searching images in databases using visual content. The advantages of the proposed method of dendrograms are: less processor time, higher quality clustering. However, along with the advantages of the dendrogram method, in the present work, an obvious drawback of this method is noted - the need to use RAM for storing the basic structure of the algorithm (matrix of compositional similarity coefficients).

In [3], the results of segmentation of ultrasound medical images based on the Canny contouring method are presented. The Canny algorithm consists of four stages: image blur (the dispersion of additive noise in the image is reduced); differentiating the blurry image and calculating the gradient values in the x direction and y direction; not maximum suppression; threshold processing. In fact, this is a set of sequentially applied algorithms. This approach is resistant to noise and usually gives better results compared to other methods. But since this is just a set of algorithms, the speed of this method is inferior to simpler operators.

The advantage of the proposed algorithm is the minimization of the level of errors, ensuring the finding of most boundaries; maximum accuracy of selection, that is, ensuring a minimum distance between the detected and actual boundaries; the only response in a place where there is only one border.

The Canny algorithm has a two-level threshold for trimming redundant information. This drawback does not allow the Canny algorithm to be used in automatic mode, since the required participation of the user in setting the upper and lower thresholds is required.

In [4], a method for analyzing medical images based on the Laplassian contouring was proposed. 1st and 2nd order Laplacian - the method is focused on sharpening graphic data. The main goal of sharpening is to emphasize small details or to improve those details that were out of focus due to errors or imperfections in the method of digitizing medical data. The method is based on the application of the first or second derivatives.

Proposed by the authors, the method has high speed image processing and relatively low computational complexity. In addition, for this method, parallelization of calculation processes is easily applicable. High speed, ease of calculation, parallelization of processes gives a great advantage in the application of this method for processing data in layers.

The disadvantage of this method is that the value of the relative number of erroneously determined contour pixels of this method decreases nonlinearly. A mathematical model of noise is proposed in [5], and then the result of removing artificially added noise using various filters is compared. The proposed noise model is essentially a multiplicative noise that changes not 1 pixel, but a group of adjacent pixels in the range from 0 to 9 along each axis. The authors compare the developed model with standard multiplicative noise. Real ultrasound image is processed by averaging filter. Multiplicative noise is applied to one copy of the resulting image filtering, and multiplicative noise proposed by the authors is applied to another. Artificially noisy copies of the filtered image are compared with the original image by the standard deviation criterion (MSE).

Based on the table of reduced MSE values for 5 different images, it is concluded that the model proposed by the authors is more accurate than standard multiplicative noise.

It should be noted that the proposed model does not have a normal distribution, by technical means, at the moment, it is impossible to completely suppress it, therefore, the approach to the development of methods based on artificially created images is theoretically poorly justified.

In [6], the authors solve the problems of modern diagnostics based on ultrasound images, referring to their earlier studies: the human factor, specific noise and the general low definition of the edges of objects in the image. It is noted in the materials of the article that, based on research by Shrimadi and others, the authors of the paper draw conclusions about the percentage error of all ultrasonic measurements, setting it from 9% to 36%. To solve this problem, the authors developed a system. The system presented by the authors, on the basis of the proposed method of anisotropic diffusion, filters the noise of the ultrasound image and then, based on the method of analysis of global and local histograms, segments the ultrasound image. However, the paper does not provide a description of the experimental testing of the system, nor does it provide numerical test results.

In [7], a search is made for points on the edge of an object based on polynomial interpolation of its boundaries on the image that is filtered and filtered by a Gaussian filter. The boundary point is the point at which both interpolation curves intersect. The authors do not define the general principle of searching for the points of the curves used to construct the polynomial, the sizes of the "inter-pixel interval", as well as cases when the selected curves do not intersect, or intersect at several points. From this we can conclude that the points should be selected so that in the selected interval there are no sharp fluctuations in brightness caused by noise. The paper gives numerical examples using Gaussian filters of various sizes on curves with a length of 5 to 20 pixels. But the main disadvantage of this method is the restriction on the exact definition of the upper and lower levels. For a signal outside the edge that is not smooth and also contains some noise, the signal level is calculated as the average of several points. These points should be symmetrical around the reference level (input, initial) of the intersection point. The distance and number of pixels from which the average value is determined depending on the task.

In [8], a method for isolating contours on ultrasound images of the heart was proposed. The proposed processing algorithm begins with smoothing the image with a 9 × 9 Gaussian filter, and normalizing the result. Then a new image is generated as follows. For each point of the normalized image, the maximum "polar difference" is calculated, which is defined as the difference in brightness of diametrically opposite pixels in a variety of directions (8 neighborhoods are probably used). For the resulting values, the maximum "polar difference" is again calculated, and it is subtracted from the values obtained in the previous step. The result is scaled logarithmically for visual perception. The effectiveness of the algorithm proposed by the authors is determined on the basis of visual comparison with the result of the expert.

The main advantage is the short processing time, since this algorithm does not require re-smoothing the image to obtain a pronounced peak. The disadvantage of this algorithm is that it does not give a single, precisely defined contour of the object, but makes the boundaries of strong brightness differences more noticeable.

Approaches to binarization of images are no less diverse than to cleaning from noise. There are a huge number of histogram conversion algorithms, adaptive local and global threshold filters based on various statistics and parameters. In [9], the authors used a morphological dilatation filter to eliminate "narrow troughs" of brightness values in the image. The authors proceed from the fact that the brightness of the lumen pixels is characterized by a low average intensity and a low standard deviation, the adventitious pixel brightness is characterized by a high average intensity and a low standard deviation, and the remaining pixels must have a high average intensity and a high standard deviation. As a result, the authors obtained a two-dimensional histogram of the image of the carotid artery. For each pixel, we considered a 10 × 10 environment by which the mean value and standard deviation were calculated. The mean and standard deviation were normalized from 0 to 1 and grouped into 50 classes in the 0.02 interval. The authors in the classification according to the values of 2 parameters attributed: the arterial lumen pixels by the average brightness value to the first class, and by the standard deviation value to the first to seventh class. Thus, the work performs segmentation by the threshold of statistical quantities. An important advantage of this approach is its efficiency in processing low-contrast images, as well as images for which it is necessary to apply a variable binarization threshold.

The disadvantage of the algorithm is the limited class of application, since the main requirement for its use is the continuity and smoothness of the contour of the desired object.

In [10], a method for distinguishing the contours of objects in low-contrast blurry images was proposed. Generalized method is as follows. Two images of one scene with varying degrees of blur are subtracted from one another. Points obtained by subtracting the "image" at which the sign will change are considered the contours of the objects of the original image. A comparative evaluation was carried out by the standard deviation and peak signal-to-noise ratio. Noise and blurring of test images was carried out in the Matlab program, using a Gaussian filter and white noise (according to the Gaussian distribution).

The advantage of the proposed method is that the method allows to reduce the width of the contour line and increase the accuracy of its localization.

The disadvantage of the proposed method is an increase in processing time and an increase in memory, since the algorithm works with two images (input and blurry). In [11], segmentation of ultrasound medical images based on global and local histograms. Initially, it is proposed to establish 4 brightness ranges, each of which will correspond to certain objects in the image: 1 - cavities filled with water; 2,3 - areas of medium echogenicity (mainly muscle tissue, which can be both hypo-and hyperechoic); solid inclusions (bones, calculi). The image is preliminarily filtered, then its histogram is approximated. It does not specify what kind of low-pass filtering yields an image, nor does it refine the method of approximating the histogram. Then, according to a principle that is not specified, local minima are determined and threshold values are set for the above 4 brightness ranges. Then the image is analyzed by a window of 7x7 or 9x9 pixels, for each of which local histograms are built. Pixels are excluded from the obtained histograms, the number of which in the window does not exceed 5% of all pixels in the window. Then, the number of local maxima in the obtained histograms is calculated. If more than 1 local maximum is found, the point-center of the window is recognized by the contour; if the local maximum is 1, the point-center of the window refers to the type of object to which the local maximum of the histogram of its window belongs.

The main advantage is that the algorithm provides high segmentation accuracy based on the analysis of local histogram statistics, since the obtained limit line has a less complex shape, does not contain gaps, and there are no random "holes".

The disadvantage of this method is the low visual information content, which does not make it possible to widely apply it.

In [12], the question of choosing the dimension of the mask of weight coefficients was solved in the method of sharpening low-contrast images. The authors proposed a method for sharpening low-contrast two-dimensional images. Differences in brightness of one pixel wide are obtained by processing the image with a sliding window with weights that are calculated separately for each pixel in the image. To analyze the dependences of the accuracy of the sharpening method on the size of the weight mask used in it, an artificial generated, noisy and blurry image was used. As a result of experiments with masks of various sizes, it was concluded in the work that the size of the mask must necessarily coincide with the width of the differences in image intensities. When choosing a larger mask, the selected contours are more rounded than the true ones and cover large areas. The advantage of the proposed approach is that it allows you to work with low-contrast images, sharpen them, while providing a width of the intensity difference of one pixel, and also to highlight the contours that provide the determination of geometric parameters with high accuracy.

The disadvantage is that when you select a smaller mask, the image becomes grainy, erroneous contours appear.

Another algorithmic approach to segmentation was proposed in [13], namely, an algorithm for threshold image processing was proposed that calculates the threshold using a special type of histogram called the "three-peak histogram of the intersection points of the original and the smoothed image". A smoothed image is obtained from the original using Gaussian filters.

An important advantage of the algorithm is that it allows you to automatically determine the threshold value as a result of approximating a portion of a three-peak histogram, this indicates its adaptive nature. That is, this allows you to apply it not only for threshold processing, but also for highlighting the image outline.

The disadvantage is that the principle of selecting the size of the Gaussian filter mask is not specified, nor is the formula for obtaining the set of intersection points of the original and the smoothed image based on which a three-peak histogram constructed. It is proposed to set the brightness threshold value equal to the brightness corresponding to the maximum value of the average peak of the three-peak histogram.

An adaptive filter based on the anisotropic diffusion method was proposed in [14], which changes the threshold value of the diffusion coefficient and automatically sets the number of iterations depending on the image noise level. The results presented by the authors show the effective operation of the filter for images of the noise level up to 90% of the signal level compared to the anisotropic diffusion filter, which uses a randomly selected threshold value and the number of iterations, which allows optimizing the filter parameters.

The advantage of an adaptive filter based on anisotropic diffusion using an adaptive threshold value and a function of the number of iterations allows you to obtain an image with preserved edges of small objects even at a noise level of 90% of the signal amplitude. The disadvantage of the proposed method is the occurrence of computational complexity in the context of lowering the speed of the algorithm depending on the number of iterations.

In [15], a genetic algorithm (GA) was proposed that automates the process of constructing ultrasound image segmentation methods. GA finds solutions with a predetermined processing result. A parallel genetic algorithm for finding correspondences between the values of texture parameters of images and processing methods suitable for them is also proposed. The result of the two aforementioned GAs is a set of image processing sequences and the corresponding vectors of texture parameter ranges.

The advantage of the algorithm under consideration is that it allows achieving a segmentation quality close to expert for a given ultrasound image (90% match).

The disadvantage of the parallel genetic algorithm is that it allows with a high degree of certainty (probability ≥ 0.8) to obtain the desired processing result, provided that the parameters of the given image are close enough to the parameters of any image from the training sample.

In [16], a method of secondary processing of various types of images is proposed, which makes it possible to distinguish contours characterized by a maximum value of the brightness difference. When visualizing ultrasound images, the bulk of the information is contained in the differences in brightness. In this case, the psychophysical properties of vision are such that the contrast sensitivity depends on the intensity of the surrounding background and, therefore, the reaction of the eye to a change in illumination is non-linear [1]. The above leads to the fact that when highlighting the boundaries of objects and conducting geometric measurements, a systematic error arises related to the peculiarities of human vision. This error can be eliminated using the secondary processing of ultrasound images.

This method can significantly reduce the systematic errors of the geometric measurements of the heart associated with the psychophysical features of a person's vision.

However, the application of this method in medical practice leads to the fact that for different types of images characterized by texture features and saturation, the efficiency of border extraction can be different. In [17], the results of experimental studies of the influence of features of human vision on the measurement error of the geometric dimensions of objects with a blurred outline are presented. The study was conducted in a group of 11 operators. Each participant was asked to choose the point at which, in their opinion, the maximum value of the brightness difference is observed in several test images. Images were offered to operators in a loop in order to average the error value on the same image. The results of the study confirm the need to create supporting software designed to reduce the subjectivity of expert analysis of ultrasound images.

In [18], segmentation is performed on an ultrasound image of layers of artery tissue in order to measure their thickness. The experiments were carried out on 100 ultrasound longitudinal images of the coronary artery, the results of computer calculations were compared with the measurements of two experts, and no significant differences were found in the computer and expert assessment. Testing of the method was carried out as follows. On each of the images, a region containing the artery wall was manually selected. The selected area was filtered to eliminate noise using the filters described in, then it was binarized, the binarized image was dilated over a 3x3 set, the borders at the bottom of the selected area were eliminated, and a contour was drawn using B-splines. As a result, selected tissue boundaries were obtained. Statistical calculations of deviations in computer and expert assessment of tissue thicknesses in various ultrasound images of the artery are also presented. However, the results of the proposed method were not presented for less "good" cases of ultrasound of the arteries, on which there is no such clear difference in the brightness of the layers of the artery. As a result, selected tissue boundaries were obtained.

In [19], a GA was proposed for obtaining effective threshold detectors for signal identification, which is also applicable in image processing and machine vision problems. GA is used to study compound operators used in the task of identifying objects. The proposed results show that GA is one of the methods for synthesizing complex operators that allow recognition of objects. In order to generate noise / target classification rules and object identification rules, the GA algorithm is also used. The algorithm is used to extract dependent features from a plurality of predefined sets of image features. The algorithm is used to obtain automatic object recognizers. In [20], the statement of the problem of segmentation of medical magnetic resonance images is presented. A hybrid ant algorithm for its solution is proposed, which allows to improve the quality and speed of image processing. In solving the problem, the methodology of swarm intelligence, cluster analysis, the theory of evolutionary calculations, mathematical statistics, computer modeling and programming are used. The authors present the results of experiments obtained on the basis of data from a library of medical MRI images. The optimal values of the parameters determining the behavior and efficiency of the algorithm are established.

Advantages of the algorithm: the comparative simplicity of the actions performed, the possibility of a highly efficient implementation for multiprocessor architectures, guaranteed convergence (although the convergence time is not defined).

The disadvantages are mainly associated with not always optimal settings. Meanwhile, the objects on MRI images have a high degree of complexity and multifactoriality, which imposes high requirements on the reliability and accuracy of their research.

In [21], the implementation and analysis of a mixed algorithm for segmentation of K-medium and ant colonies was performed, and a software system for visualizing and testing the developed algorithm was implemented. The developed algorithm was tested on public benchmarks (Berkeley benchmark was used). The output processed images are obtained, as well as the values of the heuristic coefficients of the developed algorithm.

As can be seen from the results presented by the authors, the proposed method coped quite well with the task. The advantage of the algorithm is the correct separation of parts of the image from the background. However, as can be seen from the presented results, in order to achieve the optimum, the method still needs the correct selection of heuristic parameters. The study of the functions and features of modern specialized systems for the analysis and processing of medical images for various purposes has shown that these systems have several disadvantages. The main drawback seems to be that most of the systems contain only a wide range of image analysis and processing methods available to the researcher, without indicating which method should be applied to achieve the conversion goal. In this regard, the following problems were identified: it is impossible to guarantee the optimal (in the sense of achieving the conversion goal) the choice of a method (or combination of methods) for image processing, since this choice is based only on the knowledge and experience of the user; it is impossible to search all the methods available to the researcher (and their combinations) to achieve the best processing result, since it will be too time-consuming.

3 Research method and results

The result of the Fuzzy C-Means algorithm is that each pixel in an image is assigned a vector of the function of membership to each class, with reference to which we can make a conclusion about the nature of the object, but subject to the previous neutralization of the influence of the noise factors. Currently, there is no single approach to the task solution. In [22] it is suggested that Wiener filtering is used, and in [23] the use of adaptive anisotropic filtration is proposed. The main problem is the fact that a-priori knowledge of spectral characteristics of both noise and noise-free (i.e. ideal) images is required for optimal filtering. In this regard, the method of selective singular decomposition of automorphic visualization (AVSSDM) [24-26] of noisy images is of interest, because this method does not require a-priori knowledge of spectral characteristics, but only approximate knowledge of the noise correlation interval.

AVSSDM is relating to the image analysis framework methods with the size of the square frame corresponding to the correlation interval. A multidimensional array is formed on the basis of AVSSDM, to which a procedure for decorrelation transformation is applied with the formation of a new array of "own" images. The first "own" image corresponding to the highest singular value is taken as the filtered image.

The experimental findings given in [27] were applicable to the analysis of geophysical fields images. The informational capabilities of the method as applied to the analysis of ultrasonic pulse-echo images remained unclear.

Therefore, for the further improvement of efficiency of medical diagnostics, it is necessary to investigate the information capabilities of AVSSDM and fuzzy FCM clustering as applied to the tasks of medical ultrasonic pulse-echo image segmentation.

The fuzzy clustering is a generalized version of the traditional C-means algorithm overcoming the constraints of group membership of the samplings. The fuzzy clustering uses a fuzzy set in order to specify the degree of membership of the samplings to only one group. The numerical value of the degree of membership lies in the range [28-30], so that the sum of all values of membership of one element (pixel) to all groups is equal to unity.

The fuzzy clustering algorithm is based on the use of procedure for iterative minimization of the objective function

$$J(U,V) = \sum_{i=1}^{c} \times \sum_{n=1}^{N} u_{in}^{m} \left| x_n - v_i \right|^2 , \quad (1)$$

where $V=\{v_1,\ldots,v_c\}$ – cluster centers; $U=[u_{in}]$ – matrix of order $c\times N$, where u_{in} is the membership function i of n entry x_n, $m\in[1,\infty)$ – fuzzification parameter, C – assigned cluster count. The values of the membership functions should satisfy the following constraints:

$$0 \le u_{in} \le 1\,,\ i = 1,2,...,c\,,\quad n = 1,2,...,N\,; \tag{2}$$

$$\sum_{i=1}^{c} u_{in} = 1\,,\quad n = 1,2,...,N\,; \tag{3}$$

$$0 < \sum_{n=1}^{N} u_{in} < N\,,\quad i = 1,2,...,c\,. \tag{4}$$

This iterative algorithm is based on the sequential computation of the following equations:

$$v_i = \frac{1}{\sum_{n=1}^{N} u_{in}^{m}} \sum_{n=1}^{N} u_{in}^{m} x_{in}\,,\quad i = 1,2,...,c\,; \tag{5}$$

$$u_{in} = \frac{\left[\dfrac{1}{\left|x_n - v_i\right|^2}\right]^{1/(m-1)}}{\sum_{j=1}^{c}\left[\dfrac{1}{\left|x_n - v_j\right|^2}\right]^{1/(m-1)}}\,;\ i = 1,2,...,c\,,\ n = 1,2,...,N\,. \tag{6}$$

For each pixel in the ensemble of images, the value of its membership function for each cluster depends on the distance to the corresponding center of the cluster. The fuzzification parameter m reduces the influence of low values of the membership function. The advantages of the Fuzzy C-Means algorithm can include its flexibility, which allows to work with values of membership functions. The disadvantages include the need to assign a-priori cluster count and the theoretical uncertainty of the choice of initial values and fuzzification parameter, resulting in the variant results of clusterization, as well as noise sensitivity.

The Figure 1 a-d shows the ultrasonic pulse-echo image of the child's brain (a) and the first three "own" AVSSDM images (b-d) in "space-time" coordinates. Such echo-impulse images are usually considered as a set of signal paths (image columns). It is apparent that the original image on the Figure 1a is noisy, whereas on the first "own" AVSSDM image (Fig. 1b) the influence of modulation distortion is virtually neutralized. When considering the amplitude-time slices (Fig. 2 a and b) of the 50th impulse line (50th column of the Figures 1a and 1b), one can see removing excessive noise from a signal (Fig. 2b) (rapidly changing amplitudes in peaks and declines (Fig. .2a)).

The Figure 2 c and d shows the amplitude-time slices of the second and third "own" AVSSDM images (Fig. 1c, d) corresponding to the noise components, and their rejection is actually equivalent to the adaptive filtration effect, since no assumptions were made about the spectral and statistical characteristics of the modulation noise [31-33].

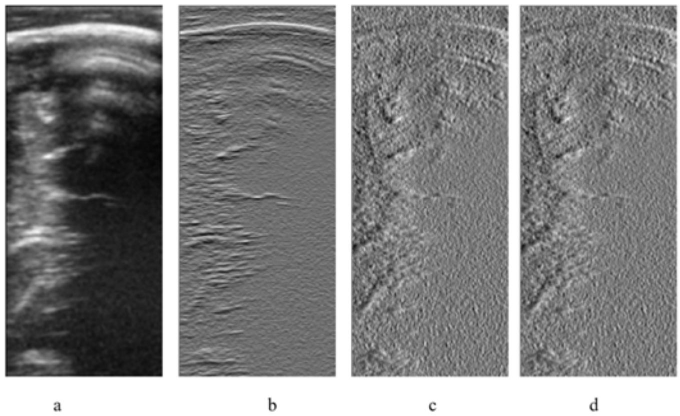


Fig. 1. Ultrasonic image of the brain: a – original image; (b – d) – first three “own” images synthesized based on the application of AVSSDM (horizontal axis is a space axis; vertical axis is a time axis)

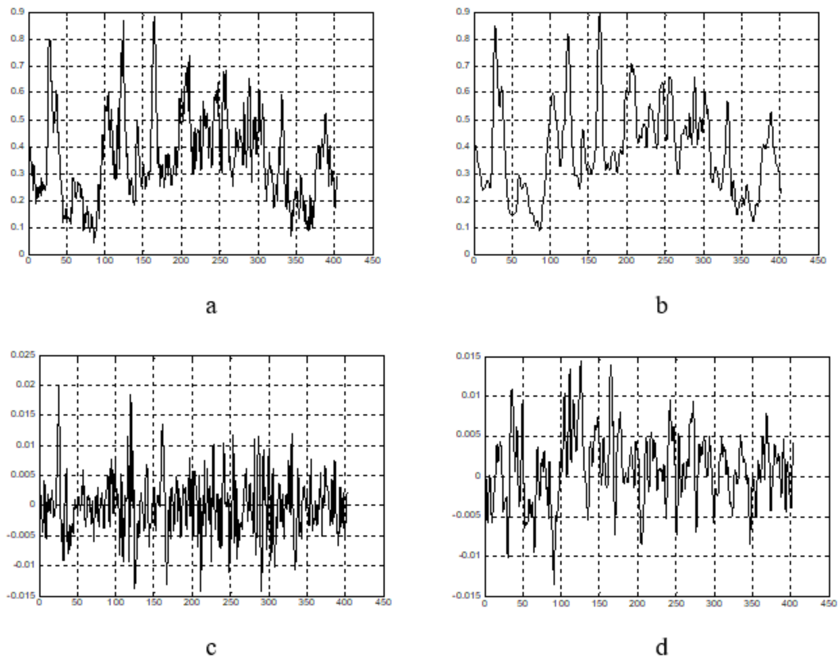
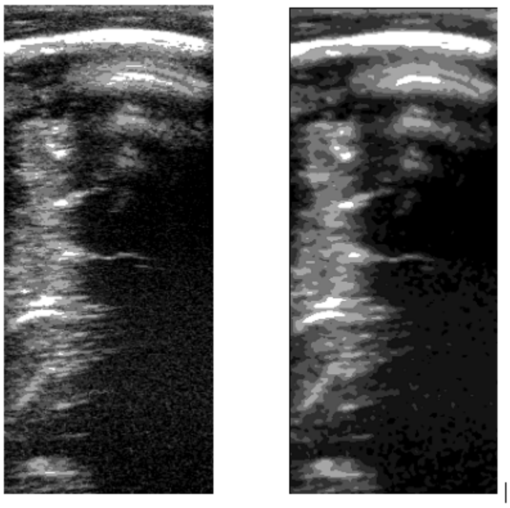


Fig. 2. Amplitude-time slices of the 50th impulse line of the images on the Figure 1 a-g, respectively (horizontal axis is a space axis; vertical axis is a relative amplitude)

The Figure 3 depicts the results of the application of the fuzzy clustering technique for segmentation of Fig. 1a and Fig. 1b into seven classes



a b

Fig. 3. Results of the application of the fuzzy clustering technique: a – Fig. 1a; b – Fig. 1b

It follows from the comparison of Fig. 1a and Fig. 3a that the application of the fuzzy clustering technique for segmentation of the noisy image actually accomplishes nothing, whereas its application to the filtered image (Fig. 3 b) allows to facilitate the procedure for visual analysis and interpretation of diagnostic results e.g. by varying the number of classes [34 - 39].

4 Conclusion

The fuzzy clustering technique is a fairly simple and convenient method for improving the efficiency of the procedure for visual analysis of medical ultrasonic pulse-echo images. The neutralization of the influence of modulation noises is an indispensable prerequisite for the successful application of the fuzzy clustering technique. The method of selective singular decomposition of automorphic visualization of noisy images is an effective method of modulation noise filtering, because this method does not require a-priori knowledge of spectral and statistical characteristics

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